Online-Appendix zu

„Measuring the Impact of Carbon Emissions on Firm Value Using Quantile Regression“

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Appendix

Table 9: Complete quantile regression results

Decile	Variable	Model 1 Coef.	Model 1 p-value	Model 2 Coef.	Model 2 p-value	Model 3 Coef.	Model 3 p-value
1	Carbon Emission*	-0.004	0.174	-0.087	0.000	-0.005	0.039
	Growth	0.443	0.000	0.420	0.000	0.438	0.000
	Leverage	0.330	0.000	0.343	0.000	0.332	0.000
	Profitability	2.717	0.000	2.741	0.000	2.728	0.000
	Capital Intensity	-0.018	0.699	-0.054	0.304	-0.006	0.916
	Liquidity	0.656	0.000	0.586	0.000	0.652	0.000
	R&D Intensity	4.035	0.000	4.058	0.000	4.028	0.000
	Constant	0.714	0.000	0.748	0.000	0.716	0.000
2	Carbon Emission	-0.008	0.035	-0.144	0.000	-0.010	0.009
	Growth	0.655	0.000	0.635	0.000	0.649	0.000
	Leverage	0.261	0.000	0.305	0.000	0.255	0.000
	Profitability	3.649	0.000	3.725	0.000	3.635	0.000
	Capital Intensity	0.020	0.735	0.010	0.867	0.020	0.790
	Liquidity	0.734	0.000	0.732	0.000	0.716	0.000
	R&D Intensity	5.651	0.000	5.647	0.000	5.643	0.000
	Constant	0.793	0.000	0.820	0.000	0.802	0.000
3	Carbon Emission	-0.008	0.019	-0.164	0.000	-0.008	0.004
	Growth	0.880	0.000	0.855	0.000	0.879	0.000
	Leverage	0.286	0.000	0.325	0.000	0.281	0.000
	Profitability	4.134	0.000	4.148	0.000	4.110	0.000
	Capital Intensity	0.072	0.223	0.089	0.234	0.070	0.355
	Liquidity	1.108	0.000	1.056	0.000	1.105	0.000
	R&D Intensity	6.505	0.000	6.708	0.000	6.476	0.000
	Constant	0.833	0.000	0.856	0.000	0.839	0.000
4	Carbon Emission	-0.010	0.000	-0.156	0.000	-0.010	0.000
	Growth	1.081	0.000	1.047	0.000	1.073	0.000
	Leverage	0.319	0.000	0.309	0.000	0.320	0.000
	Profitability	4.508	0.000	4.635	0.000	4.498	0.000
	Capital Intensity	0.173	0.002	0.153	0.068	0.173	0.043
	Liquidity	1.393	0.000	1.372	0.000	1.413	0.000
	R&D Intensity	8.345	0.000	8.390	0.000	8.338	0.000
	Constant	0.849	0.000	0.880	0.000	0.851	0.000

5	Carbon Emission	-0.012	0.000	-0.162	0.000	-0.010	0.000
	Growth	1.225	0.000	1.213	0.000	1.230	0.000
	Leverage	0.241	0.000	0.242	0.002	0.255	0.000
	Profitability	4.683	0.000	4.722	0.000	4.711	0.000
	Capital Intensity	0.262	0.000	0.240	0.003	0.266	0.014
	Liquidity	1.819	0.000	1.811	0.000	1.827	0.000
	R&D Intensity	9.479	0.000	9.409	0.000	9.478	0.000
	Constant	0.905	0.000	0.937	0.000	0.901	0.000
6	Carbon Emission	-0.016	0.000	-0.189	0.000	-0.014	0.000
	Growth	1.621	0.000	1.549	0.000	1.599	0.000
	Leverage	0.170	0.027	0.237	0.004	0.175	0.041
	Profitability	5.006	0.000	5.120	0.000	4.987	0.000
	Capital Intensity	0.236	0.021	0.212	0.011	0.236	0.015
	Liquidity	2.089	0.000	2.210	0.000	2.090	0.000
	R&D Intensity	11.051	0.000	11.048	0.000	11.014	0.000
	Constant	0.998	0.000	0.999	0.000	1.001	0.000
7	Carbon Emission	-0.021	0.000	-0.220	0.000	-0.019	0.000
	Growth	1.886	0.000	1.829	0.000	1.888	0.000
	Leverage	0.034	0.694	0.049	0.629	0.035	0.750
	Profitability	5.578	0.000	5.629	0.000	5.558	0.000
	Capital Intensity	0.226	0.004	0.188	0.028	0.221	0.002
	Liquidity	3.041	0.000	2.920	0.000	3.025	0.000
	R&D Intensity	11.279	0.000	11.486	0.000	11.266	0.000
	Constant	1.114	0.000	1.158	0.000	1.119	0.000
8	Carbon Emission	-0.031	0.000	-0.260	0.000	-0.025	0.000
	Growth	2.467	0.000	2.444	0.000	2.457	0.000
	Leverage	-0.209	0.048	-0.234	0.029	-0.217	0.066
	Profitability	6.341	0.000	6.334	0.000	6.368	0.000
	Capital Intensity	0.197	0.090	0.168	0.303	0.194	0.119
	Liquidity	3.623	0.000	3.536	0.000	3.588	0.000
	R&D Intensity	12.136	0.000	12.142	0.000	12.206	0.000
	Constant	1.350	0.000	1.401	0.000	1.356	0.000
9	Carbon Emission	-0.055	0.000	-0.409	0.000	-0.045	0.000
	Growth	2.876	0.000	2.821	0.000	2.848	0.000
	Leverage	-0.535	0.003	-0.502	0.019	-0.528	0.012
	Profitability	6.779	0.000	6.669	0.000	6.698	0.000
	Capital Intensity	0.427	0.008	0.390	0.061	0.396	0.122
	Liquidity	4.665	0.000	4.607	0.000	4.701	0.000
	R&D Intensity	12.816	0.000	12.766	0.000	12.795	0.000
	Constant	1.778	0.000	1.836	0.000	1.789	0.000

Table 10: Correlation matrix

	Overall	Scope1	Scope2	Growth	Leverage	Profit.	Cap. Int.	Liquidity	R&D Int.
Overall	1.00								
Scope1	0.97	1.00							
Scope2	0.69	0.58	1.00						
Growth	-0.12	-0.11	-0.17	1.00					
Leverage	0.20	0.19	0.19	-0.09	1.00				
Profit.	0.03	0.02	0.08	-0.34	-0.04	1.00			
Cap. Int.	0.03	0.04	-0.05	0.32	0.09	-0.30	1.00		
Liquidity	-0.23	-0.22	-0.24	0.29	-0.38	-0.31	0.07	1.00	
R&D Int.	-0.19	-0.18	-0.20	0.36	-0.25	-0.55	0.12	0.56	1.00

Table 11: Variance inflation factors

Variable	Model 1	2	3
R&D Intensity	1.99	1.99	1.99
Profitability	1.66	1.65	1.66
Liquidity	1.64	1.64	1.64
Growth	1.30	1.30	1.30
Leverage	1.25	1.26	1.25
Capital Intensity	1.19	1.19	1.19
Carbon Emission*	1.08	1.09	1.09

*Carbon Emission denotes the emission category used in respective model

Quantile Regression with non-additive effects

The combination of quantile regression and panel data analysis allows to provide more flexible and informative results than classical panel data models (Koenker 2004). This is because additional to the possibility to control for unobserved individual-specific effects as in standard panel data models, quantile regression allows to expose heterogenous covariate effects. Thus, heterogeneity is addressed at both the population and the individual level (Huang et al. 2017). However, it is a special challenge to estimate a fixed effects model in the context of quantile regression (Huang et al. 2017). In mean regression, it does not pose any problem to include additive fixed effects in panel data models to control for unobserved individual-specific heterogeneity (Powell 2015). In contrast, if additive fixed effects are included in a quantile regression model, as done in most approaches including Koenker (2004), Canay (2001) and Kato et al. (2012), the resulting model

$$y_{it} = \boldsymbol{x}_{it}\boldsymbol{\beta} + \alpha_i + \varepsilon_{it} \quad \text{with} \quad Q_y(\tau|\boldsymbol{x}_{it}, \alpha_i) = \alpha_i + \boldsymbol{x}_{it}^T\boldsymbol{\beta}(\tau) \qquad [5]$$

is not comparable to the cross-sectional quantile regression model introduced in section 3. This is because the calculated quantile estimator for panel data indicates the effect of an independent variable at different quantiles of the distribution of $(Y_{it} - \alpha_i)|\boldsymbol{X}_{it}$ instead of $Y_{it}|\boldsymbol{X}_{it}$ (Powell 2016). These results cannot be interpreted in the same manner as the cross-sectional quantile estimates introduced above. To address this problem, a quantile regression model for panel data with so-called nonadditive fixed effects was introduced by Powell (2015). In this approach, the nonseparable disturbance term that allows the parameters to vary among the quantiles and typically motivates classic quantile regression, is maintained. By separating α_i from the disturbance term as in [5], the parameters are only allowed to vary based on one part of the disturbance term, while the other part is exclude just because it is fixed over time (Powell 2016).

Powell (2015) overcomes this problem by combining both the individual-specific effect and the observation-specific disturbance term in a not further defined function ε_{it}^{*}:

$$\varepsilon_{it}^{*} = f(\alpha_i, \varepsilon_{it}) \qquad [6]$$

As the nonseparable disturbance term is remained, the resulting conditional quantile function has the same structure as the one obtained from cross-sectional quantile regression:

$$Q_\tau(y|\boldsymbol{x}) = \boldsymbol{x}\widehat{\boldsymbol{\beta}}_\tau \qquad [7]$$

Thus, the calculated quantile estimators for panel data can be interpreted in the same manner as cross-sectional quantile estimators and still control for unobserved individual-specific fixed effects. As the model solely controls for the fixed effects but does not estimate them, the number of parameters that have to be estimated is relatively small compared to most panel data regression model. Moreover, it is one of only a few models that provide coefficient estimates that are consistent for comparably small amount of time-series (Powell 2015; Baker 2016).